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An approach for the integration of anticipative maintenance strategies within a production planning and control model

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Abstract

Current production planning and control systems of manufacturing companies do not include future-oriented maintenance strategies that allow the precise prediction of maintenance tasks. This results in inefficient production processes due to unforeseeable machine downtimes, fluctuating lead times and a high number of rush orders. An approach for the integration of anticipative maintenance strategies within a production planning and control model is developed in order to increase the flexibility and quality of production planning. Based on an anticipative maintenance strategy, the model derives measures for minimizing the overall production costs as well as maintenance related costs over a finite planning horizon.

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Keywords: Maintenance;Production planning and control; Predictive model; Integrated planning models

1. Introduction

Today's companies face the challenge to model their production processes flexible, versatile and customer oriented, in order to stay competitive. This leads to challenges, like the increasing of facility complexity, decreasing of lead time, higher variance of production and assembly processes, rising claims regarding quality as well as cost pressure [1]. Especially the decrease of lead times causes an increasing of capacity and flexibility demands in production [2]. Beside the quality of products, customers begin to perceive logistics performance measures, like the adherence of delivery dates or lead time, as a criterion for decision making. 67% of enterprises prioritize lead time already as the most important target dimension [3].

Even though the strong interaction between production planning and control (PPC), maintenance and quality management is scientifically proven [4,5] and its influence on the above described challenges is undisputed, current planning processes are conducted without a holistic approach that considers all three areas. This results in non-aligned maintenance and production plans. Wrongly picked maintenance dates influence the productivity of a production system significantly. An ideal trade-off between maintenance- and production related costs cannot be found. Beside choosing inefficient moments for planned maintenance measures, short-term changes of during the production processes represent main reasons for turbulences on the shopfloor. As an example, the average planning reliability of SMUs specialized on mechanical engineering, averages 25% after only three days [6]. A big stake of those changes result from unplanned facility downtimes, which restrict the demanded flexibility of a production system significantly. Hence delays emerge which are difficult to compensate and cause additional costs (e.g. due to bad product quality or avoidable overtime)

Furthermore, the ability of employees, to act and react on those unexpected occurrences, is often limited. Decision-making that is not based on a reliable data basis leads to uncoordinated manual interventions and therefore inefficiencies, undefined and not manageable processes.

The depicted difficulties on the shopfloor-level (Fig. 1) lead to an increase of urgent orders and high deviations in

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lead time. If the quantity of urgent orders increases by 35%, the processing time of normal orders, rises up to 40%, depending on the stock level [7].

In the long term, a significant decline in delivery dates is the consequence. An often-used approach is to compensate this effect with earlier order releases. However, this kind of countermeasure leads to a rising stock level, an overstressing of resource capacities and an increasing of lead-time due to longer queues in front of machines. The internal dynamic increases and the effect amplifies additionally. The trend of declining delivery dates, is hence not stopped, but contrary enhanced. The production performance is declining exponentially [8].

2. State-of-the-Art on integrated planning models

The overall performance of a production system depends significantly on effective planning and process design on the shop floor-level [5,9].The essentially influencing factors on among others are production planning and control, maintenance and quality management. Many literature sources prove the strong interaction of these disciplines with regard to productivity, product quality and aggregated costs of a production system [10].

During the past years different problem-solving approaches were developed, which aim to support production planning and control in terms of various target values. Hadidi et al. distinguishes currently existing models in two groups [11]:

1) Interacting models: These models aim on optimization of a defined function under the consideration of other functions. The requirements of other functions constitute restrictions for the model.
2) Integrated models (Fig. 2): These models aim on the optimization of two or even more elements at the same time.

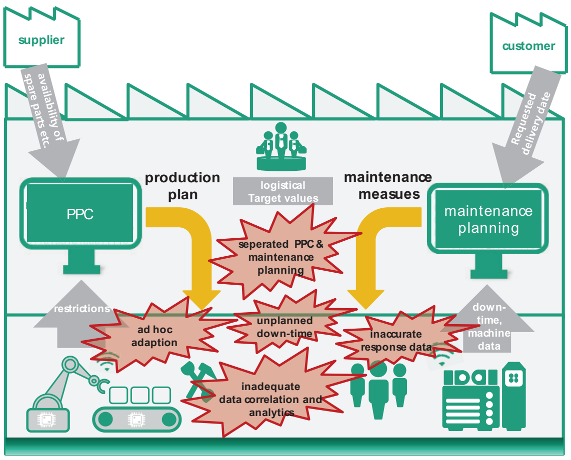

Fig. 1. Current difficulties caused by a lack of integrated PPC & maintenance planning.

Fig. 2. Interaction of relevant functions to plan and control production.

2.1 Interacting models in area I (production planning and maintenance)

Zhou et al. present a dynamic-opportunistic maintenance model for a multi-component system, were the maintenance planning is able to react on short-term changes in production order sequences. Short-term alterations in the production schedule are inevitable due to market fluctuations and can therefore lead to prioritization or deferring, of preventive maintenance operations. The components of the system interact respectively support each other, with the result that a preventive maintenance operation causes a shutdown of the whole system. Once this condition occurs, the model will suggest additional necessary maintenance operations on the system, to guarantee that the opportunity costs, caused by maintenance operations, are as low as possible [12].

Aghezzaf et al. attend to solve the problem of incomplete maintenance operations by using a non-linear mixed-integral optimization model. Therefore, a single machine, on which corrective and preventive maintenance operations are carried out, is observed. It is assumed, that the condition of the machine is stochastically determinable and hence the number of necessary maintenance operations within a planning period, can be calculated based on the system's age. The model considers the number of necessary maintenance operations as well as the condition of the machine in terms of the system's reliability, as additional restrictions in production planning and control. Furthermore Aghezzaf et al. provide a tool to measure the performance of this heuristic approach. This is especially interesting for an integration into an ERP system of a company [10].

Wong et al. contemplate a production process with heterogeneous machines, which place distinct requirements on maintenance operations: The machines demand different maintenance measures, which cause diverse downtime. Furthermore, the chronology between measures varies from machine to machine. With the aid of a genetic algorithm, this difficulty is depicted and the cycle-time is minimized. The model assumes that maintenance operations are "perfect", which means that the condition of the machine is set "new" after a conducted maintenance measure [13].

Xiao et al. draft an optimization model, which particularly focuses on the difficulties of interlinked facilities: If a facility is down due to a preventive maintenance operation, the whole production line stands still. The model cumulates necessary maintenance measures on various machines with the result that they can partially be conducted simultaneously. The effect of cumulative measures is then compared with the effect of measures conducted sequentially. The goal is a holistic decrease of production costs, costs for preventive maintenance measures, repair costs and opportunity costs, caused by delays in process operations [14].

2.2 Integrated models in area III (maintenance planning and quality management)

Nourelfath et al. developed an optimization model that additionally considers the aspect of product quality. The observed system consists of an error-prone facility, whose status can be described either "in control" or "out of control". As soon as the machine's status is "out of control", requirements regarding product quality cannot be satisfied. The deterioration of the facility is described by the Weibull function: It is assumed that maintenance measures are imperfect and hence improve the condition of the facility by a certain percentage. The model tries to find the optimal trade-off between (i) frequently conducted maintenance measures who lead to a decrease of quality-related costs, but increase costs for maintenance, (ii) rarely executed maintenance measures who cause an increase of quality-related costs and (iii) production of faulty parts who are increasing production costs [15].

2.3 Integrated models in area II (production planning, quality management and maintenance)

Matyas presents a procedural approach for anticipative maintenance planning by building conclusions based on the interaction between condition- and load data, historical quality- and machine data as well as the medium-term planning of production. With the interlinkage of real-time PLC-, data from production planning, condition monitoring and process data as well as historical quality- and machine failure data it is possible to achieve the best possible product quality, optimized plant availability and reduced maintenance costs. This methodology is applied in a maintenance control center for production lines in order to anticipate failure and reveal deviations in quality on real-time basis [16]. This approach is supported by a dynamic wearout calculation of a machine component to determine the remaining useful lifespan of a machine component [17], as well as data analysis and simulation in order to quality relevant cause and effect coherences [18].

2.4 Summary on existing models

Despite different research activities, weak spots exist, that prevent the applicability of currently existing planning models in the operational praxis as well as the receipt of realistic results: 1) The general validity of the presented models is missing. In most approaches very specific framework conditions are assumed which usually cannot be generalized for other environments. 2) Many models are based on assumptions, which do not prevail in realistic production scenarios. Hence, the validation of a majority of those models is conducted by numerical examples. Praxis relevant examples which quantify the benefit for companies are often missing. 3) Restrictions and dependencies between facilities are partly ignored. Many approaches refer to single machines; a combination of parallel and serial interlinked facilities is not considered. 4) Currently existing planning algorithms calculate dates for maintenance based on stochastic, theoretical methods (e.g. Weibull-distribution). State of the art knowledge regarding predictive/anticipative maintenance is often not considered in most of the presented approaches. The de facto condition of facilities regarding components is hence not observed. 5) The interaction and the holistic optimization of the areas production planning, maintenance and quality management is not considered sufficiently in currently existing models. 6) A majority of key researchers point out that the high level of computational power of developed models poses a challenge for integration into ERP-, PPS- and MES-Systems. 7) The topic of data acquisition and processing via suitable interfaces is not considered, although it is seen as a major challenge in today's praxis due to lack of data quality, heterogeneous data structures and non-linked systems.

Beside the attempts of creating holistic planning models and logics for PPC, research activities exist, which focus on the design of software-architectures with the purpose of real-time data acquisition, -aggregation and -processing for production enterprises. With the current development in direction of "Smart Factory", it becomes necessary to react fast and flexible on changing environmental conditions and interruptions in the system. Todays applied systems, in the area of PPC and maintenance, do not satisfy those requirements [19]. In terms of PPC, this means that decisions are made based on inaccurate planning results, which were calculated from historical data and assumptions [3].

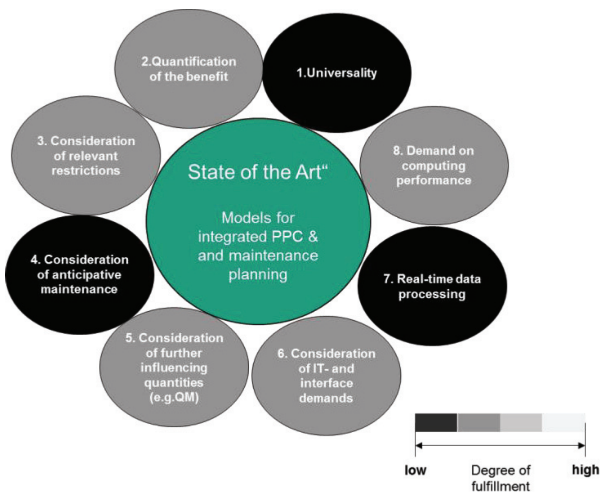

Fig. 3. Identified need for research.

Research activities in this area contribute a big step towards real-time capable planning systems, nevertheless ignore the underlying tangible planning algorithms that describe reciprocities and create forecasts. This is caused by the fact, that the already designed IT-architectures are created to cover a broad field of application. They provide hard- and software concerning framework conditions to implement a real-time capable "smart" solution, where it is required to lodge tangible policies and solution algorithms, for specific fields of application. It should be questioned and validated whether the necessary data storage and data processing capacity satisfies the particular applications.

A combination of the above described planning models with suitable real-time capable software-architectures would lead to a compensation of weak spots of currently used planning systems and hence create significant added value for enterprises. Summarizing, the following research demand can be derived from the current state of the art (Fig. 3).

3. Towards integrating planning models: A concept for TCM based production scheduling

For a long time, maintenance was not considered a top priority neither in science nor in practice; it was much more seen as a fire fighting [20]. In the last decades, however, the importance of maintenance has changed. At the very beginning, maintenance was used as a reactive tool: repair measures were performed when a failure occurred. Since production equipment became more expensive, down times were getting more costly and reactive maintenance was no longer cost efficient. Therefore, preventive maintenance was developed in order to reduce the downtime costs. However, maintenance costs also rose dramatically with the increase of the equipment's complexity. Thus, the current development of maintenance is intended to predict failure times of an equipment's critical parts and to perform maintenance measures only when they are truly necessary.

Despite the change in the importance of maintenance, the framework in which it is embedded has remained static, as it was shown in section 2. Maintenance exists in parallel with PPC and quality management and synergies are hardly ever used. Production sequences, for example, currently originate from PPC systems; they particularly originate from detailed production scheduling which is mostly generated by manufacturing execution systems (MES). Those production sequences are optimized concerning different criterions such as order finish dates, productivity and costs. However, the condition of machines and their tools is hardly taken into account and possible subsequent quality-related work (due to a too worn tool) is accepted, or production sequences are frequently adapted at shopfloor-level via "go and see" planning. However, the ability of employees, to react to unexpected occurrences and reschedule the production program is limited; thus, suboptimal decision-making leads often to uncontrollable processes.

To forestall this negative development in a sustainable way, the number of currently necessary, short-term rescheduling operations must be reduced dynamically. Unplanned facility downtimes as well as machine tool wear depict a main reason for rescheduling. However, rescheduling can be decreased by conjunction and evaluation of maintenance relevant data as such as real-time machine data, condition monitoring data, historical data as well as historical knowledge about machine tool wear and downtime occurrences. These data can be used to predict necessary maintenance measures and times. In a further step, the proposed maintenance measures can be coordinated with PPC to find an optimal time for maintenance measures and to optimize production sequences. However, this real-time conjunction does not exist yet. An additional difficulty is that currently used ERP- and MES-systems are not able to react on unexpected and all of a sudden occurring events. Optimization algorithms, which constitute a core element of planning models, are often based on statistical coherences and historical data, so the actual prevailing conditions in production are disregarded.

A possible way of integrating PPC and maintenance and deal with the above described problems depicts the concept that we developed and which will be presented in the following (Fig. 4).

Within the proposed concept, machine components' and machine tools' conditions are evaluated by calculating their Health Points. Furthermore, the products are assigned to minimum Health Points in order to optimize production sequences and maintenance times.

3.1. Concept part a: Condition Monitoring System

Condition Monitoring of critical machine components and production tool condition monitoring (TCM) of equipment and fractal production systems (FPS) as well as its assignment via Health Points is executed in figure 3 (a). Within the first part, sensor data, as for example vibration signals, is collected and saved in a database; the sensor data is continuously analyzed in time-domain within a condition monitoring system. The analyzation outcomes are Health Points, which describe the constitution of a certain machine's component or machine tool. The term "Health Points" was consciously chosen in order to build a rhetorical bridge to the topic gamification [21].

What is more, products are assigned to minimum Health Points (HP_{min}) of specific machine components and tools. Whilst some products need a high amount of Health Points in order to be produced, others are not Health Point-dependent. In addition to this, products also decrease the Health Points (ΔHP) of machine components and tools in dependence of the product's characteristics when they are produced. Therefore, each product is assigned with HP_{min} and ΔHP for each FPS' tool or component. Furthermore, other product information such as delivery date and storage costs is taken into account and integrated with machine data (current and further predicted FPS' Health Points). This combination of TCM and products' Health Point assignment could then be used to optimize the FPS' production sequences.

3.2. Concept part b: FPS' Communication

However, such an optimization on FPS-level only would create partial optima, but stocks and waiting times would emerge between the FPS. To reach an optimum of the whole

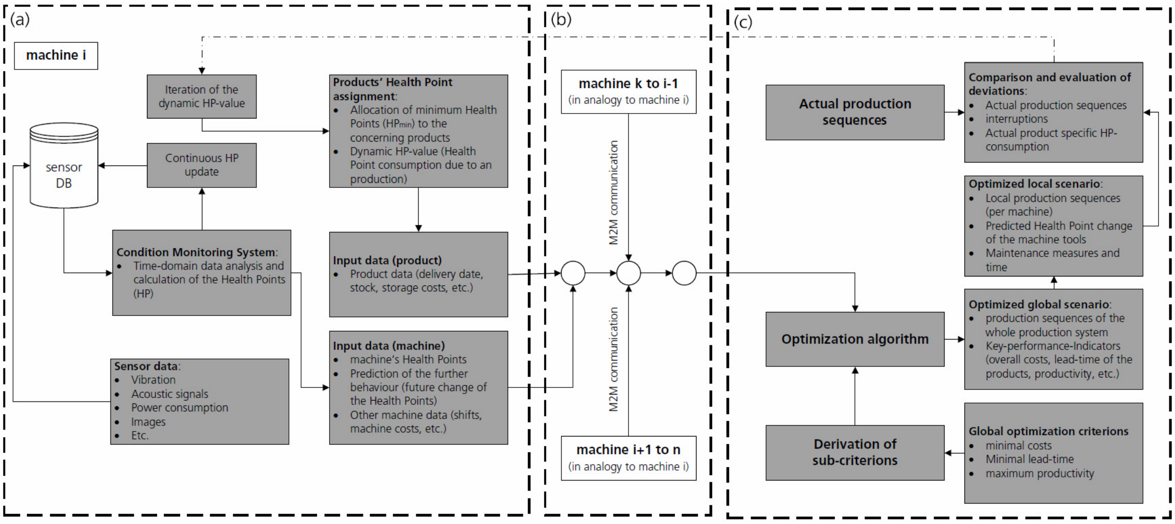

Fig. 4. (a) Condition Monitoring System; (b) FPS' Communication; (c) global production sequence

production system, communication between the FPS have to be enabled. As shown in figure 3 (b) data and information is exchanged between the FPS via machine to machine (M2M) communication. To cope with this huge amount of data, it is firstly decentrally cumulated (at FPS-level) and only necessary information is exchanged with neighboring fractal production systems. Therefore, FPS *i* communicates with the up-stream (concerning the value stream) FPS k to *i-1* and with the down-stream ones *i+1* to *n*.

3.3. Concept part c: global production sequence optimization

In Fig. 4 (c) a global optimization criterion is defined, as it is common in PPC (e.g. cost, productivity, lead time, etc.) and derived into sub-criterions within a paramount algorithm. Those sub-criterions are integrated with the exchanged information of the neighbouring FPS; the integrated data is then used to calculate an optimized global scenario. Thus, the global scenario contains the production sequences of the whole production system as well as some Key Performance Indicators such as overall production costs, productivity etc. In a further step, the global outcomes are used to derive local scenarios, which contain production sequences as well as maintenance measures and times at FPS-level.

In order to create a system's intelligence, the optimized production sequences are compared to the actual production sequences and differences are used to iterate the dynamic HP value (ΔHP) in order to refine further predictions. In addition, the optimization algorithm is refined iteratively.

4. Use-case

In section 3 a concept of TCM-based production scheduling was described. In the current section, the first development stage (a) is presented in more detail.

Imagine a partly worn machine tool can no longer be used to manufacture products with high quality requirements (e.g. low tolerance, damageable material). However, it can still be . used for machining products with lower requirements. But, what is the best time to maintain a machine tool? This question becomes even more important since the maintenance actions are becoming more time and cost consuming due to the tendency of increasing equipment's complexity. As described in section 3, one can see that in the proposed concept production sequences particularly depend on two different variables: On the one hand, they depend on the condition of the machine tools (Health Points). On the other hand, they depend on the specific requirements of the products themselves (products' Health Point assignment).

4.1. Health Points

There are various technological possibilities to measure a machines' condition, which mostly depends on the machines' specific characteristics. In literature as well as in the field different sensor signals are used for this measurement for example vibration data, acoustic signals, power consumption or even images [22,23]. However, literature concerning condition monitoring of machine tools is sparse; an example for TCM stems from Dimla et al. who use vibration signals to derive the condition of cutting tools [24].

During the development of the aforementioned concept, we started with the implementation of the condition monitoring part. Therefore, we measured vibration signals of an industrial plate shears in order to determine the condition of the shears. Therefore, the gathered data was analyzed within time-domain; it showed, that there is a correlation between the vibration signal and the shears' condition (the more worn the shears, the higher the vibration amplitudes during cutting). To transfer the data into information and decrease the required memory, the data was cut-wise cumulated and used to create the Health Points basic scale. Whilst a high value in Health Points means a good condition of the shears, a low rating can be seen as a worn-out condition. The Health Points are used as a (close to) real-time assignment of the shears' condition as well as to predict the further behavior and the RUL (Rest of Useful Life).

4.2. Products' Health Point assignment

To enable a TCM-based production scheduling the certain products have to be assigned at least the minimal FPS' tools' Health Points. Due to the ongoing trend in industry of growing variants, production systems have to be adapted to the product variants' varying demands. As briefly described in section 3 some damageable or high-quality products, for example, need tools in mint condition for machining; partly worn tools would not fulfil the necessary quality as for example low tolerances.

5. Conclusion and future outlook

In this paper, a concept to integrate anticipative maintenance strategies within PPC has been developed. For the evaluation of the concept a use-case was set up. Within the use-case, a production tool condition monitoring system has been set up for mechanical plate shears. Their condition is visualized by the so-called Health Points. For the integration of this TCM-based maintenance strategy and PPC, the products have been categorized according to their needs in Health Points in order to derive a decision support for the possible production program. The products' Health Point assignment in the current development stage is limited to a single machine. The proposed concept of the TCM-based production scheduling has a positive impact on the overall production costs because of reduced effort for rescheduling, reduction of rework and scrap as well as the reduction of stock and therefore a shortened leas-time.

The next development stage will be focusing on the integration of more than one fractal production system within the use-case and enabling an information exchange between them. Thus, an optimization can be achieved among the whole system consisting of multiple FPS.

In order to achieve a holistic optimization of the whole production system the TCM-based production scheduling needs to be integrated within a companies IT systems landscape. At this moment, usually this means an implementation in an existing PPC of MES tool. In the light of developments such as Industrie 4.0 and smart factories, future research is necessary how anticipative maintenance strategies may be integrated within an autonomous production system.

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